Journal of Technology and Informatics (JoTI)
Vol. 8, No. 1, Bulan April Tahun 2026
P-ISSN 2721-4842
E-ISSN 2686-6102

Brush-shaped Motion Gesture of UGV Using Hand Gesture Recognition

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Article Information

Article History:
Received : 12 December 2025
Revised : 23 January 2026
Accepted : 5 February 2026
Published : 6 April 2026

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Keywords:
Observation, UGV, KNN, *Gesture Control, Brush-shaped, Smart farming*

10.37802/joti.v8i1.1315

Journal of Technology and Informatics (JoTI)
P-ISSN 2721-4842
E-ISSN 2686-6102
https://e-journals.dinamika.ac.id/index.php/joti

***Abstract*:**

Manual observation of corn leaf diseases in agricultural fields often faces challenges related to time, effort, and accuracy. To address these challenges, brush-shaped motion patterns, such as zig-zag and boustrophedon trajectories, provide an effective solution by enabling uniform area coverage while reducing redundant traversal, energy consumption, and sensing gaps, making them well-suited for precision agriculture applications. Building on this approach, the system utilizes the MediaPipe framework for hand landmark tracking and the K-Nearest Neighbors (KNN) algorithm to recognize six navigation commands: forward, backward, stop, turn_right, turn_left, and capture. These commands are transmitted via Wi-Fi with an average latency of 0.001964 s. To ensure navigation accuracy during pattern execution, corrections are made using rotary encoders. Gesture classification experiments on 6,000 samples achieved a maximum accuracy of 99.46% across two participants, with stable KNN performance under both indoor and outdoor lighting variations, as well as hand distances ranging from 50 cm. Furthermore, the capture gesture produced an average image acquisition latency of 0.3037 s at various UGV observation positions. In summary, these results demonstrate that integrating real-time gesture control with UGV maneuvers enables systematic field surveys for maize leaf disease monitoring and supports Sustainable Development Goal (SDG) 2 through precision agriculture technology.

INTRODUCTION

Pest and disease attacks on maize crops are among the primary factors contributing to reduced agricultural productivity and significant economic losses. Effective management requires accurate and timely information on plant conditions; however, the localized development of disease symptoms and their uneven spatial distribution often complicate manual field observations [1]. As the demand for more efficient monitoring systems continues to grow, research on unmanned technologies, including Unmanned Aerial Vehicles (UAVs), Unmanned Surface Vehicles (USVs), and Unmanned Ground Vehicles (UGVs), has advanced rapidly over the past decade. These systems enable autonomous or semi-autonomous operation across diverse terrain conditions without the need for direct human intervention, particularly in environments that are inefficient, hazardous, or difficult to access [2]. Intelligence within these systems is implemented through machine learning. This approach enables machines to learn from data in order to recognize patterns and make informed decisions, as demonstrated in various applications such as cyber-threat classification [3]. The advancement of these technologies aligns with the concept of smart farming, which has become a key pillar in strengthening global food security and supporting the achievement of Zero Hunger (SDG 2). Smart farming integrates intelligent sensors, automated monitoring, and precision control to enhance the efficiency and sustainability of crop production. The study "Smart Farming Towards a Sustainable Agri-food System" emphasizes that technological integration within the agricultural sector represents a strategic pathway for building a resilient food system by optimizing production processes and improving product quality [4].

Previous studies have implemented joysticks, remote controls, and motion sensors such as Motion Processing Units (MPUs) in UGV control systems; however, most of these studies were conducted at the laboratory scale and paid limited attention to outdoor environments, including variations in lighting, constraints on operator mobility, and the need for flexible interaction across large maize fields [5]. These conditions highlight the need for control methods that do not rely on additional physical devices. With the advancement of unmanned vehicle technologies, UGVs are increasingly considered as more adaptive platforms for supporting field monitoring activities. UGVs are generally equipped with various environmental sensors and are capable of performing both autonomous navigation and teleoperation for applications such as surveillance, logistics, and hazardous material handling across diverse terrain conditions [6]. In terms of human-robot interaction, hand gesture recognition has emerged as an effective non-verbal communication method. Gestures are analyzed based on palm orientation, finger positions, and specific hand configurations to serve as instructions for the system [7].

MediaPipe enables gesture recognition without the need for additional specialized devices while remaining efficient on platforms with limited computational capabilities. For the classification stage, the K-Nearest Neighbors (KNN) algorithm was selected due to its stability against data variations, its ability to handle relatively small datasets, and its effectiveness in preserving the geometric structure of the data through Euclidean distance computation [8]. These characteristics make the combination of MediaPipe and KNN suitable for UGV control implementation in outdoor maize fields with varying lighting conditions. Many gesture-based UGV control systems implement five primary gesture labels [9], and this study extends that set by introducing the *"capture"* gesture as a trigger for field image acquisition.

Related studies on gesture-based UGV control have reported varied outcomes. Xu [10] developed AIP-Net, a two-stage top-down anchor-free network that employs an FCOS-based BodyDetector within a RetinaNet50-FPN architecture to detect human body parts in complex environments. This method achieved 97% accuracy in real-time UGV control, including 180° rotational maneuvers based on hand positioning, while maintaining high efficiency through the use of only six convolutional layers. Nevertheless, the approach still relies on large-scale datasets to attain optimal performance. Unlike the neural network-based approach in the previous study, this research implements a structured gesture-based UGV control workflow, including hand image acquisition, landmark feature extraction using MediaPipe, classification via the KNN algorithm, and mapping of classification results to UGV navigation commands. Therefore, the distinction of this study lies not only in the number of hand positions but also in the processing workflow and the classification approach employed for real-time UGV control.

Meanwhile, CNNs have been shown to achieve up to 99% accuracy in facial recognition [11]. This study adopts KNN due to its computational efficiency and suitability for classifying gestures based on discrete geometric features on resource-constrained devices. The integration of KNN within deep neural networks has been explored to enhance model robustness against adversarial attacks. These findings underscore the importance of preserving the data manifold structure in feature space to maintain model stability. Implementation of KNN on simple datasets, such as MNIST, has been reported to achieve 95% accuracy, demonstrating that the use of the Euclidean distance metric can effectively maintain the geometric integrity of the data [12]. K-Nearest Neighbors (KNN) research achieved the second-highest relevant classification accuracy of 63.15%, surpassing XGBoost. This result confirms the effectiveness of KNN in recognizing local patterns based on geometric proximity within dimensionally reduced feature spaces. However, the findings also indicate that KNN predictions tend to be less precise and stable, and are more sensitive to variations in distance metric selection and data dimensionality [13]. Fuad (2023) employed a CNN-based approach for upper-body gesture recognition, achieving 92% accuracy across five basic navigation gestures for robotic control [9].

Building on these developments, this study proposes a semi-autonomous hand-gesture control system integrated with MediaPipe and KNN to operate a UGV using a brush-shaped motion pattern, implemented through zigzag maneuvers, to enhance maize leaf disease monitoring coverage. The study expands the gesture set to six by adding the "capture" command and employs a rotary encoder to perform position corrections during navigation across uneven terrain. Utilizing a dataset of 6,000 samples representing gesture variations under diverse conditions, the research aims to deliver a more intuitive, responsive, and precise control system that supports precision agriculture while making a tangible contribution to achieving the SDG Zero Hunger target.

METHOD

This chapter's research methodology ensures a structured, replicable experimental process. Each stage—gesture dataset collection, MediaPipe landmark detection, KNN-based classification, and PID correction—follows consistent procedures to ensure valid data and minimize bias. Evaluation methods at each step support a robust assessment of system performance.

Gesture Dataset Collection

The research dataset consists of 6,000 hand-gesture images. These were divided into 70% for training and 30% for testing. The data include variations in palm and finger configurations. Images were collected from two participants of the same gender, each performing a range of hand positions matching the defined classes. All samples were classified into six gesture categories, representing UGV control commands. Gesture images were captured using an M-TECH WB350 webcam at a resolution of 640×480 pixels. The lighting and background were controlled to ensure image consistency and minimize visual interference. The dataset covers six predefined gesture classes: "forward", "backward", "stop", "turn_right", "turn_left", and "capture". For data management and labeling consistency, the dataset was organized in a hierarchical directory structure. Each gesture class was stored in a separate directory, with directory names directly representing the gesture labels [14]. Figure 1 presents the flowchart of the dataset acquisition process, which involved capturing 500 images per session. The directory generated from the dataset acquisition process consists of six separate folders. Each folder is labeled according to the corresponding gesture class. The dataset collection process indicates that data acquisition for all classes was conducted within a single, structured, and continuous session. Each folder stores a collection of sample images associated with a specific gesture class. This organization creates a well-structured dataset for subsequent training and validation of the classification model. The resulting dataset directories are shown in Figure 2. The dataset used in this study contains six gesture classes, each with 1,000 samples, totaling 6,000 samples. This balanced distribution helps avoid bias during model training and ensures each gesture is equally represented. As a result, the model can learn the characteristics of each gesture class, improving system stability, accuracy, and generalization in recognizing tested gestures. The number of samples for each hand gesture class is presented in Table 1.

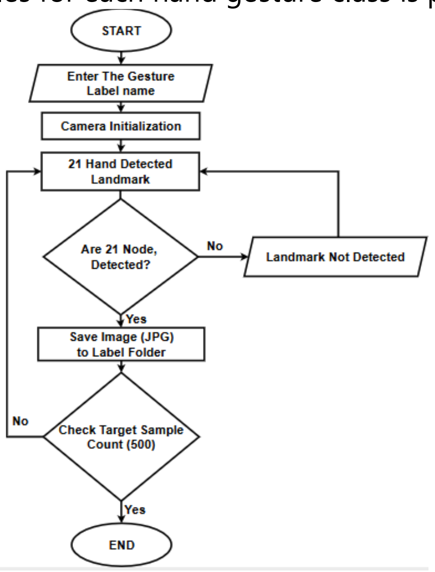


Figure 1. Flowchart Dataset Collection

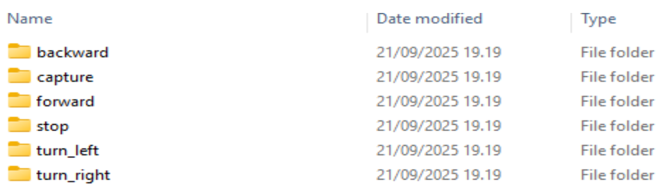


Figure 2. Folder Datasets

Table 1. Number of Datasets for Each Class

No.	Gesture	Data Amount
1	forward	1000
2	backward	1000
3	stop	1000
4	Turn_right	1000
5	turn_left	1000
6	capture	1000
Total		6000

MediaPipe Landmark Detection

The feature extraction process from the hand image dataset ended with a Comma-Separated Value (CSV) format. This was achieved through a series of systematically designed stages. Each image was then labeled according to its gesture class. All key-point data and labels were stored in a CSV file as the final output. This step is essential for preparing data for machine learning model training. It transforms visual representations into a numerical structure that computers can process. The methodology also standardizes data by minimizing variations in lighting and background. As a result, the analysis focuses on the geometric patterns and dynamics of hand gestures. This approach uses 21 hand landmark points, aligning with widely used marker-less hand tracking methods. It provides numerical representations for hand movements in gesture recognition and motion analysis applications [15]. Figure 3 illustrates the complete workflow of the feature extraction process.

MediaPipe provides three-dimensional coordinate information (X, Y, and Z) for each landmark, enabling a more accurate representation of hand position and orientation. These coordinates are then used as input features in both the feature extraction process and the gesture classification stage. This workflow is supported by MediaPipe Hands, a framework developed to detect and track hand positions in real time. In this approach, the hand is modeled using 21 landmark points that represent key anatomical positions, including the wrist, thumb, index finger, middle finger, ring finger, and pinky [16]. To facilitate reference, each landmark point is assigned an index from 0 to 20, as illustrated in Figure 4.

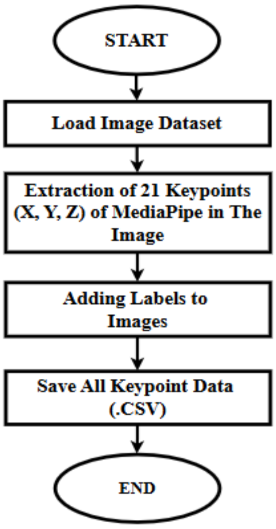


Figure 3. Flowchart of Extracting Features

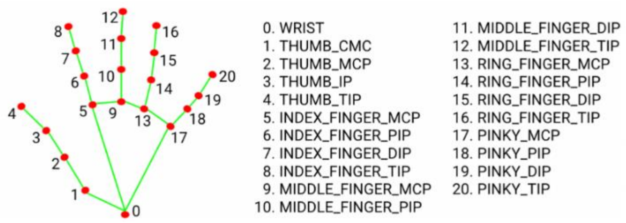


Figure 4. MediaPipe Hand Landmark [17]

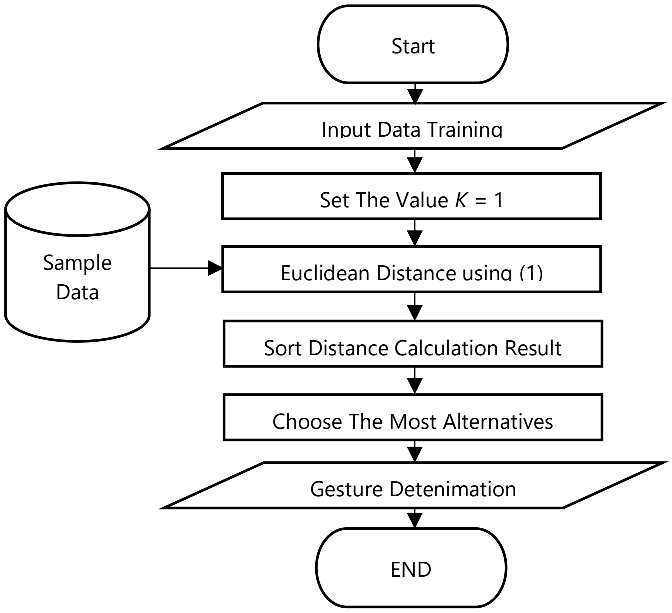


Figure 5. The Architecture of KNN

Method Gesture Classification

This study applies the K-Nearest Neighbor (KNN) algorithm to classify feature vectors obtained from hand landmark points. The selection of KNN is based on its simplicity, the absence of complex training procedures, and its ability to provide relatively stable performance on datasets with specific feature distributions [18]. To further optimize performance, various distance metrics were investigated. The Euclidean distance metric was ultimately chosen after experiments with alternatives such as Manhattan and Minkowski, as it produced the most stable results. In addition, an evaluation of *K* values ranging from 1 to 15 revealed that Euclidean distance achieved the most stable performance at *K* = 1. The architecture of the KNN process is illustrated in Figure 5. Euclidean distance is used to measure the similarity between test data and training data within the feature space [19]. The Euclidean distance formula used in this study is presented in the following equation.

$$d_i = \sqrt{\sum_{i=1}^{p} (x_{2i} - x_{1i})^2} \tag{1}$$

Information:

d_i : The distance between the two samples in space

p : Total number of features

x_{1i} : Sample test data

x_{2i} : Training data samples

This calculation process is performed to determine the differences required to obtain the Euclidean distance. The training sample with the smallest d_i value is selected as the nearest neighbor and is used to determine the class in the KNN algorithm [20]. The calculations of precision, recall, F1-score, and accuracy are used as performance measures to evaluate the results of the KNN classification method. The formulas for these metrics are presented in the following equations.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - score = 2x\frac{Precision * Recall}{Precision + Recall} \quad (4)$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (5)$$

Information:
TP : True Positive
FP : False Positive
FN : False Negative

PID Controller

The Proportional–Integral–Derivative (PID) controller is a classical control method employed in this study to maintain the robot's motion along a straight-line trajectory by minimizing deviations from the desired path [21]. The PID flowchart used is shown in Figure 6.

RESULTS AND DISCUSSION

The results of this study begin with the training dataset, testing dataset, real-time robot testing, zigzag movement testing of the robot, and the "capture" acquisition of maize leaf disease images.

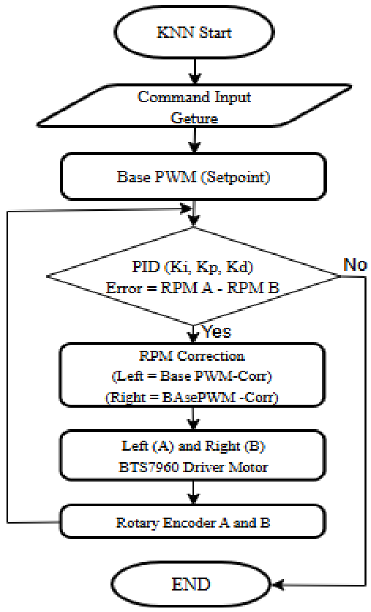


Figure 6. PID Correction

Training and Testing Dataset Results

The evaluation of the K-Nearest Neighbors (KNN) algorithm with K = 1 demonstrated good performance. Testing showed that the three distance metrics, Euclidean, Manhattan, and Minkowski, achieved 100% accuracy, although the Euclidean distance consistently exhibited more stable performance across different K values. Training results are presented in Table 2. The evaluation of the K-Nearest Neighbors (KNN) testing model with K = 1 demonstrated excellent performance, achieving 99.46% accuracy the highest value across two different participants, as shown in Table 3.

Table 2. Training Data Evaluation Result

Gesture	Precision	Recall	F1-Score	Support
forward	1.00	1.00	1.00	320
backward	1.00	1.00	1.00	286
stop	1.00	1.00	1.00	324
turn_right	1.00	1.00	1.00	287
turn_left	1.00	1.00	1.00	289
capture	1.00	1.00	1.00	304
Accuracy			100%	

Table 3. Participants One

Gesture	Precision	Recall	F1-Score	Support
forward	0.98	1.00	0.99	500
backward	0.99	0.99	0.99	500
stop	1.00	0.98	0.99	500
turn_right	1.00	0.98	0.99	500
turn_left	0.98	1.00	0.99	500
capture	1.00	1.00	1.00	500
Accuracy			0.9946	

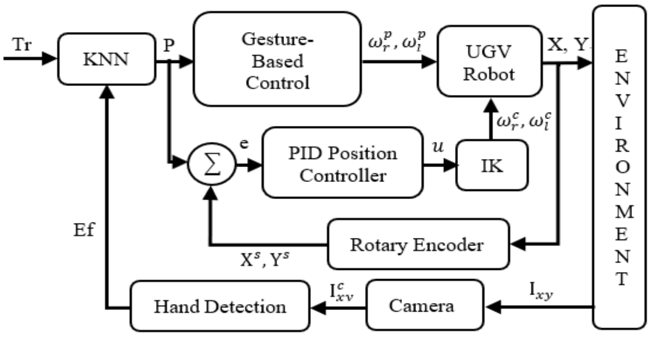


Figure 7. System Block Diagram

Real-Time Robot Testing

The block diagram of the UGV gesture control system using the KNN method is shown in Figure 7. The variables of the UGV system block diagram shown in Figure 9 can be represented in Table 4.

Table 4. System Block Diagram Variable

No.	Symbol	Information	Unit
1	u	PID Control Signal	PWM
2	Ef	Extracted Feature	.csv
3	e	Reference and Actual Position Error	m
4	I_{xy}	Hand Image in Real-Time	Pixel
5	I_{xy}^c	Hand Image For Camera	Pixel
6	P	Prediction	-
7	ω_r^p, ω_l^p	Right and Left Wheel Speed Reference	rad/s
8	ω_r^c, ω_l^c	Right and Left Wheel Speed Command	rad/s
9	Tr	Training Results	.pkl
10	X, Y	The actual position of the robot in the environment	m
11	X^α, Y^α	Position of encoder reading result	m

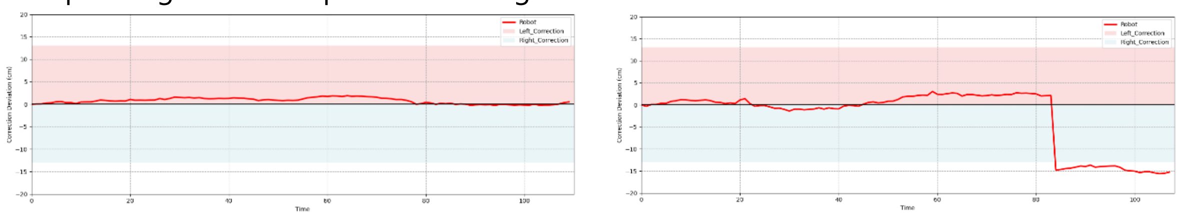
Table 5. Real-Time Gesture Recognition for UGV Robot Control

No.	Gesture	Prediction Model	Control UGV
1	forward		
2	backward		
3	stop		
4	turn_right		
5	turn_left		
6	capture		

The real-time detection test demonstrated that hand gestures captured with a single hand using a webcam could be classified and transmitted as control commands to the UGV via Wi-Fi communication, as shown in Table 5.

PID Testing of Deviation Correction

Testing on uneven terrain shows a significant performance difference between systems with and without a PID controller. By applying a PID controller with specific parameters, the system demonstrates effective lateral deviation correction, indicated by a small and stable lateral deviation around zero (±2 cm). In contrast, the system without PID produces much larger deviations, reaching up to approximately 15 cm, and is unable to return the robot to the ideal trajectory after disturbances occur. This result confirms the important role of the PID controller in maintaining the directional stability of the UGV when operating on uneven terrain. The corresponding results are presented in Figure 8.



(a) (b)

Figure 8. (a) PID Deviation Correction, (b) Deviation Correction Without PID


(a) (b)

Figure 9. (a) Operator Position, (b) Robot Performing Zigzag Movement Across the Maize Field


(a) (b)

Figure 10. (a) First capture experiment, (b) Second capture experiment

Testing of Robot Zigzag Movement and Corn Leaf Disease Capture

The UGV was tested performing brush-shaped (zigzag) movements in a maize field. Gesture-based control of the UGV was conducted remotely, with the operator positioned maximum at 5 meters away from the robot. The zigzag movement testing of the UGV robot is shown in Figure 9. Sample collection on maize leaves was also conducted in the same field during the zigzag movement tests. The results are shown in Figure 10. The results of this study demonstrate a significant performance improvement compared to previous works. Unlike the study by Fuad, which employed a CNN-based approach with five gestures and achieved an accuracy of 92%, this study extends the gesture set to six by introducing a capture gesture. It achieves a testing accuracy of 99.46% with a latency of 1.964 ms using the K-Nearest Neighbors (KNN) algorithm with $K = 1$. These results indicate excellent generalization capability despite the use of a relatively simple algorithm and outperform the accuracy reported by the Deep k-Nearest Neighbor (DkNN) method, which ranges between 94-95.5%. Furthermore, the implementation of a PID controller in the UGV control system successfully maintains lateral deviation close to zero (±2 cm), in contrast to the system without PID, which exhibits deviations of up to 15 cm. These findings confirm that conventional KNN, when combined with appropriate feature selection and Euclidean distance metrics, provides an effective, efficient, and reliable solution for real-time gesture recognition and has been consistently validated through implementation on a UGV operating in an agricultural environment. The comparison with previous gesture-based control systems is presented in Table 6.

Table 6. Comparison with the Previous Gesture-Based Control System

Study	Method	Enviroment	Additional Hardware	Accuracy/Succes Rate	Latency
M. Fuad et al. [9]	CNN	Indoor (Controlled)	Yes	92%	Not reported
Wang et al. [12]	DkNN	Simulation	No	94–95.5%	Not reported
Preposed	KNN	Outdoor	No	99.46%	1.964 ms

CONCLUSIONS AND SUGGESTIONS

Based on the experiments conducted, this study successfully implemented a hand-gesture-based control system for a UGV using the KNN algorithm. The evaluation results indicate that a K value of 1 provides the best classification performance, achieving an accuracy of 99.46% in testing on the first participant. This high level of accuracy suggests that the hand geometric features extracted using MediaPipe form a well-separated feature space, making the single nearest neighbor approach the most effective. Several factors influence the performance and accuracy of hand gesture control, including lighting conditions, hand position, and hand orientation relative to the camera. This research also introduced an additional "capture" gesture, increasing the number of gestures from five used in previous studies. Beyond gesture classification performance, the proposed UGV control system demonstrated stable robot motion. The PID controller for path deviation correction effectively reduced lateral deviation. It kept deviations small and stable around zero (±2 cm), allowing more accurate gesture command execution compared to a system without PID control. In the image acquisition process for corn leaf disease, several challenges were identified. These included unstable leaf positions, camera resolution limitations, and robot motion that can cause image blur. Still, the system successfully captured images, showing that adding the "capture" gesture is effective as a control function. The achieved accuracy is higher than the results reported in previous studies, which were lower than those of the XGBoost method.

For future work, further development of path deviation correction with PID and an added IMU sensor is recommended. This would help estimate the robot's turning position. Tests under rainy conditions, on uneven terrain, and with different crops can help evaluate the system's generalizability. Future studies may also explore other classification methods. These include SVM, CNN, Random Forest, and ANN. In conclusion, integrating the MediaPipe pipeline for feature extraction and the KNN algorithm is effective for gesture-based UGV control. This technical solution contributes to smart farming ecosystems by providing precise and adaptive field control mechanisms. It aligns with Sustainable Development Goal number 2 (Zero Hunger) by optimizing resources and strengthening food security through agricultural technology.

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